RESEARCH ARTICLE

How does digital technology empower urban green development efficiency in the Beijing-Tianjin-Hebei region—mechanism analysis and spatial effects

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Abstract

Under the strategy of "Digital China" and "Sustainable Development," the synergistic development of digital economy and green economy has become a crucial topic. Based on the panel data of 13 cities in the Beijing-Tianjin-Hebei (BTH) region from 2011 to 2019, this study investigates the direct effect, intrinsic mechanism, and spatial spillover effect of digital technology development (DTD) on urban green development efficiency (GDE). The empirical results show that (1) DTD significantly improves urban GDE in the BTH region, and it passes the endogeneity test, (2) DTD can enhance urban GDE by improving the environmental regulation intensity and technological innovation level in the BTH region; however, the industrial structure optimization weakens the promotion effect of DTD on urban GDE in the BTH region, which shows a "masking effect," (3) the kernel density estimation method and ArcGIS technology reveal the existence of "digital divide" and GDE differences among cities in the BTH region. Moreover, the spatial distribution pattern of DTD gradually forms "H–H" and "L-L" clusters in the BTH region, and (4) DTD also increases the GDE of neighboring cities through spatial spillover effects in the BTH region, and it passes the robustness test of replacing the spatial weight matrix. This study is important for the BTH region to simultaneously solve economic development and environmental problems in the context of digitalization.

Keywords The Beijing-Tianjin-Hebei region · Digital technology · Green development efficiency · Mediating mechanism analysis · Spatial spillover effect

Introduction

Currently, global warming and resource constraints are becoming increasingly severe. The contradiction between economic development, environmental protection, and resource consumption is prominent in China. Improving green and sustainable development performance is an effective way to resolve the above contradictions, and it is a crucial strategy to achieve high-quality development in China (Zhu et al. 2019; Dong et al. 2021). The Beijing-Tianjin-Hebei (BTH) region accounts for nearly 10% of China's total economy, and it is a pivotal region for China to explore green and sustainable development (Li et al. 2020). However, the BTH region has prominent problems such as high proportion of heavy industry, resource and environment overload, and serious air pollution. Meanwhile, the BTH region has a disparity in environmental quality, and cities with a high proportion of heavy industry are relatively polluted. Since the release of the Beijing-Tianjin-Hebei Synergistic Development Plan Outline in 2015, deepening the synergistic development of economy, resources, and environment has become the consensus. Liu and Dong (2021) indicated that green development is a growth mode that considers economic growth, environmental protection, and resource conservation. In

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the context of tighter resource and environmental constraints, the synergistic improvement at urban the green development level has become an essential topic to solve the contradiction between BTH's environment and economic development (Li et al. 2020). Green development efficiency (GDE) is an effective indicator to measure the synergistic relationship between economy, resources, and environment. It can effectively evaluate the performance of urban green development (Rashidi and Saen 2015). Therefore, this study aims to investigate the new drivers and temporal and spatial evolution characteristics of urban GDE in the BTH region. This can provide new empirical evidence and references for the BTH region to enhance urban GDE and formulate regional synergistic green development policies.

With the "Digital China" strategy, the synergistic development of digitalization and greening has become an inherent demand for high-quality economic and social development. The ecological modernization theory shows that digital information technology can mitigate environmental problems (Huber 2000; Popkova et al. 2022) and lays the foundation for exploring the relationship between digital technology development (DTD) and GDE. In practice, the global pandemic of COVID-19 promoted the rapid development of emerging digital technology such as cloud computing, blockchain technology, and artificial intelligence. With the energy crises and environmental problems, the role of digitalization in environmental governance has attracted widespread attention (Wang et al. 2022a), but no general consensus has been reached. The Digital China Development Report (2020) shows that during the 13th Five-Year Plan period, the value of China's digital economy core industries reached 7.8% of GDP. In 2020, internet users grew to 989 million, and the internet penetration rate increased to 70.4%. Therefore, as the frontier of China's digital development, what are the spatial and temporal evolution characteristics of DTD in the BTH region? Can DTD improve urban GDE? If this logic is valid, what are the potential mechanisms of DTD affecting urban GDE? Does DTD have a spatial spillover effect on urban GDE? Clarifying the above issues can provide a robust empirical basis and decision reference for the BTH region and even China to use digital technology to improve urban green development.

In summary, based on the panel data of 13 cities above the prefecture level in the BTH region from 2011 to 2019, this study conducts the following extended research around the potential mechanism and spatial effect of DTD on urban GDE. (1) combining the connotations of DTD and GDE, this study improves the evaluation system of DTD and urban GDE based on the reference of existing studies; then, this study uses the principal component analysis method and the super-SBM model to measure each urban DTD level and GDE, respectively, (2) after testing the direct impact of DTD on urban GDE with a fixed-effects model, this study explores the potential mechanism of DTD in urban GDE through mediator variables such as environmental regulation, technological innovation level, and industrial structure optimization, (3) this study analyzes the spatial differences and evolutionary characteristics of DTD and GDE among cities; further, the spatial Durbin model is used to identify the spatial spillover effect of DTD on urban GDE, and (4) this study performs robustness tests by replacing the spatial weight matrix, and endogeneity tests using the two-stage least-squares method after setting instrumental variables. Eventually, based on the empirical results, this study proposes corresponding suggestions and expects to provide a reference for the green development of the BTH region and even China from a digital technology revolution perspective.

The potential contributions of this study are as follows. (1) From the perspective of digitally empowered green development, this study innovatively examines the intrinsic relationship between DTD and urban GDE from both theoretical and empirical aspects. It broadens the research perspective of GDE and achieves to analyze the comprehensive effect of digital technology on economy, resources, and environment under the same framework. (2) This study explores the theoretical basis and driving mechanism of DTD on urban GDE from three aspects: environmental regulation effect, technological innovation effect, and industrial structure effect. This improves the effect path of DTD on urban GDE that has not been covered by previous studies. (3) Different from the previous static causality studies, this study uses the kernel density estimation method and ArcGIS technology to effectively reveal the dynamic temporal and spatial evolution characteristics and differences of DTD and urban GDE in the BTH region. (4) This study adds the concept of spatial location and examines the spatial correlation and spatial spillover effects of DTD on urban GDE, which deepens the study on DTD and urban GDE from a spatial perspective.

The rest of the structure is as follows. The next section is literature review and mechanism analysis to formulate the hypothesis. The third section is research design including data description, variable selection, and model construction. The fourth section is empirical tests including benchmark and mediated regression results analysis. The fifth section is temporal and spatial evolutionary characteristics and spatial spillover effect analysis. The sixth section is robustness tests. The last section is the conclusions, recommendations, and research prospect.

Literature review and theoretical mechanism

Literature review

Green development efficiency

The World Bank emphasizes that green development refers to the coordinated development of economic, social, and environmental resources by strengthening ecological protection under the constraints of ecological capacity and resource-carrying pressure (Meng and Qu 2021). As an important indicator to measure urban economic development activities, GDE can measure the performance of green development by measuring the urban input–output efficiency. Previous literature has studied the connotation (Liu et al. 2022a), measurement, influencing factors, and enhancement pathways of GDE. Regarding the measurement approach, some studies chose to construct an evaluation system to investigate the level of green development in different regions (Sun et al. 2018; Fang et al. 2020; Yang et al. 2022a). Another mainstream approach includes nonparametric data envelopment analysis (DEA) and parametric stochastic frontier analysis (SFA) (Tao et al. 2017; Zhao et al. 2020; Yuan et al. 2022). Regarding influencing factors, previous studies found that environmental regulation (Li and Wu 2017; Fan et al. 2022), fiscal decentralization (Song et al. 2018), factor distortions (Lyu et al. 2022; Lin and Chen 2018), technological innovation (Yang et al. 2022b), and financial development (Liu et al. 2019; Yang and Ni 2022) all impact GDE in different degrees. Furthermore, a few scholars studied the spatiotemporal evolution characteristics and spatial differences of GDE (Zhou et al. 2020; Liu et al. 2022a).

Digital technology development

Since Solow proposed the "Information Technology Productivity Paradox," academics have continuously debated on the utility of information technology (Wu et al. 2021), which lays a foundation for the research on digital technology. Popkova et al. (2022) indicated that digital technology includes artificial intelligence, cloud computing, information and communication technology (ICT), and other technologies. Existing studies have examined the welfare effects of digital technology from enterprise innovation performance (Usai et al. 2021), real economy development (Tian and Li 2022), green total factor energy efficiency (Gao et al. 2022), and other aspects. However, regarding the environmental effects of DTD, the few available studies have not yet reached consistent conclusions. Among them, some studies considered that DTD is beneficial to improve the environment. Liu et al. (2022b) showed that DTD not only reduces local carbon emissions but also promotes carbon reduction in neighboring cities. Wang et al. (2022b) noted that digital technology effectively contributes to energy sustainability, which is helpful to reduce SO_2 pollution. Some studies also argued that digital development requires more energy consumption and releases large amounts of CO_2, which can increase the environmental burden. Lee and Brahmasrene (2014) studied the Association of Southeast Asian Nations and noted that ICT positively affects carbon emissions. Lange et al. (2020) proposed that digitization did not decouple economic growth from energy consumption, and that the energy-increasing effect of digitization was greater than the energy-decreasing effect. Furthermore, Asongu et al. (2018) found that ICT did not significantly affect carbon emissions with data from sub-Saharan Africa.

In summary, previous studies mainly investigated the unilateral effect of DTD on economic growth, energy consumption, or environmental pollution. The following research needs to be expanded and supplemented. (1) The effect of DTD on urban GDE lacks systematic investigation. Furthermore, the indirect mechanism of how DTD affects urban GDE lacks in-depth analysis. (2) The quantitative assessment of digitalization is still weak, and single indicators such as internet penetration rate and number of websites need to be expanded (Asongu et al. 2018; Yu 2022). (3) Most studies are based on provincial and municipal samples in China and lack studies focusing on regions, which cannot reflect the imbalances and differences among cities within the region. (4) With the wide application of digital technology, DTD and GDE among cities have become more closely connected in space. However, the existing research has fewer effective explanations for their spatial–temporal evolution characteristics and spatial spillover effect. Therefore, due to the special strategic position of the BTH region in green development and digital development, this study explores the direct effect and mechanism path of DTD on urban GDE in the BTH region. Further, this study further identifies the spatial and temporal evolutionary characteristics and spatial spillover effects of DTD and urban GDE.

Theoretical mechanism and research hypothesis

Direct effect

With modern information networks as an important carrier, digital technology is the key production factor in the digital economy era. Wu et al. (2021) indicated that the Internet created by digital technology can reduce the cost

of information collection and improve the management efficiency of enterprises. In terms of system optimization, Thompson et al. (2014) revealed that digital technology can optimize production operation processes, decrease unnecessary losses, reduce negative production externalities, and thus achieve the ultimate goal of environmental protection. Digital technology provides advanced technical support for the intelligent and green transformation of enterprises, which can optimize the efficiency of resource allocation, thus reducing resource input and energy consumption (Litvinenko 2020). Li et al. (2021) proposed that the application of digital technology can diagnose and address inefficient links in the energy production, transportation, and consumption systems, thereby improving energy efficiency. The application of digital technology in socioeconomic activities such as living services, transportation operations, and industrial manufacturing can directly or indirectly reduce resource consumption and environmental pollution, which contributes to improving urban GDE (Jiang et al. 2021). For example, digital transportation systems, paperless transmissions, bike-sharing, and car-sharing can reduce unnecessary logistics and commute (Chen and Yan 2020), thus reducing energy consumption and environmental pollution. Therefore, the following hypothesis is proposed: hypothesis 1: digital technology development can positively affect urban GDE in the BTH region.

Indirect effects

Environmental regulation driving path Sareen and Haarstad (2021) deemed that environmental regulation plays a crucial role in promoting urban green development. The impact of environmental regulation on urban GDE is mainly realized through the combination of both constraint effect and innovation compensation effect (Fan et al. 2022). From the perspective of the constraint effect, digital technology has broadened the way for social agents to participate in environmental regulation and has driven a stronger implementation of environmental regulation policies and tools. It could form greater constraints on enterprises' production and operation behaviors (Wang et al. 2021). To satisfy the requirements of environmental regulations, enterprises need to increase relevant investments for energy saving and pollution reduction, which reduces the productivity and desired output level of enterprises (Zhang et al. 2018). Thus, environmental regulation negatively affects urban GDE. However, stronger environmental regulations force enterprises to increase technological innovation. Enterprises gradually form green production styles, which can improve production efficiency and operating profitability (Zhao et al. 2018). The compensation

effect of innovation promoted by increased profits offsets and exceeds the constraint effect caused by increased costs. It eventually makes enterprises improve their desired output and ecological quality level (Lee et al. 2022). Thus, environmental regulation positively affects urban GDE. Furthermore, the government improves the efficiency of environmental regulation through digital government platforms, which is helpful to improve urban GDE (Janowski 2016). In summary, the following hypothesis is proposed: hypothesis 2: digital technology development enhances urban GDE in the BTH region by increasing the intensity of environmental regulations.

Technological innovation drive path The endogenous growth theory believes that technological innovation is the main factor for the improvement of green economy efficiency. Currently, digital transformation and sustainable development effectively stimulate the market demand for green technological innovation and force enterprises to innovate production technology (Llopis-Albert et al. 2021). Proeger and Runst (2020) indicated that digital technology promotes resource sharing and information flow, and is beneficial for enterprises to acquire and integrate innovation resources. According to Schumpeter's innovation theory, the recombination of production factors is the process of achieving innovation. As a key production factor in the digital era, data resources can break through the limitations of traditional production factors and innovate production technologies and organizational models through resource reorganization (Michaels et al. 2014). Meanwhile, digital technology helps enterprises identify the direction, potential, and path of innovation. It can reduce the cost and risk of innovation and then facilitate green technological innovation. According to the new information technology paradigm, digital technology can improve the way enterprises utilize resources by accelerating technological innovation (Popkova et al. 2022). Enterprises apply innovative energy-saving and environmental protection technologies, cleaner production technologies, and pollution monitoring technologies to production systems, which can improve production efficiency and reduce negative externalities of production and environmental pollution (Wu et al. 2021). As a result, urban economic growth can be decoupled from resource consumption and environmental pollution, and urban GDE will increase. In summary, the following hypothesis is proposed: hypothesis 3: digital technology development can enhance urban GDE in the BTH region by improving the level of technological innovation.

Industry structure drive path Previous studies showed that digital technologies such as the Internet of Things

can help traditional industries reorganize factor resources, optimize production processes, and realize transformation from extensive to intensive and high efficiency (Cardona et al. 2013). The application of digital technologies such as 5G, big data, and cloud computing will also give birth to high-tech industries with low energy consumption and high added value, which will optimize the industrial structure (Yu 2022). Zhu et al. (2019) indicated that industrial structure optimization is an effective measure to realize green development. The "structural dividend" brought by industrial structure optimization benefits economic growth and improves environmental quality, thus enhancing urban GDE. Szalavetz (2019) revealed that digital technology promotes the transformation of industrial structure from labor-intensive to technology-intensive. From the perspective of production inputs, industrial structure optimization can improve GDE by reducing energy and resource consumption (Zhang et al. 2022a). From the perspective of output, the process of industrial structure transformation from low-technology to high-technology will inevitably improve environmental performance and green productivity, thereby increasing urban GDE (Gu et al. 2022). Furthermore, digital technology can break through the time and space limitations of industrial development, which is conducive to realizing nonspatial industrial agglomeration. Using the externalities of agglomeration, it can accelerate the elimination of low-quality or backward production capacity, which is conducive to driving the development of green transformation (Ding et al. 2022). In summary, the following hypothesis is proposed: hypothesis 4: digital technology development can enhance urban GDE in the BTH region by promoting industrial structure optimization.

Spatial spillover effect

OMRI (2020) indicated that digital technology can reduce inter-industry differences and spatial boundaries, thus, promoting the rapid flow of resources and technology in a wider region. Similarly, Paunov and Rollo (2016) confirmed that digital technology can enhance knowledge and technology spillover effects, promote cross-regional resource reorganization, and optimize factor allocation and production layout in adjacent regions. It has a positive synergistic effect on the urban GDE of neighboring regions. Yu (2022) showed that the Internet generates positive spatial spillover effects, which significantly promoted the industrial green productivity of local and neighboring regions. However, Zhang et al. (2022b) found that the digital economy failed to exert a spatial spillover effect on promoting the carbon performance of neighboring cities. Meanwhile, it should not be overlooked that the gap

between developed regions and backward regions in terms of DTD level is relatively large. The "digital divide" has intensified the siphoning of talents and resources by developed cities (Wang et al. 2022a). The "competition effect" between cities has led to negative externalities in space. The divergence of digital technology further widens the gap in urban GDE. In summary, the impact of DTD on urban GDE may also have a spatial spillover effect, and the total spillover effect depends on the magnitude of the two effects. Therefore, the following hypothesis is proposed: hypothesis 5: digital technology development has a spatial spillover effect on GDE in neighboring cities of the BTH region.

In the comprehensive analysis above, a mechanism diagram of DTD in urban GDE is shown in Fig. 1.

Variable definition and model construction

Variable definition

Explanatory variable: digital technology development (DTD) index

Considering the availability of city-level data, this study measures the urban DTD level in four aspects: digital infrastructure, digital factor inputs, digital technology-related outputs, and digital transaction development (Table 1), with reference to Liu et al. (2022b) and Gao et al. (2022), wherein digital transaction development is measured using the Digital Inclusive Finance Index of Peking University. Since Luo et al. (2022) indicated that the principal component analysis method can assign objective weights based on the characteristics of data and indicators, it can avoid the problems of the high correlation of indicators and subjectivity of weight structure. Referring to Liu et al. (2022b), this study uses the principal component analysis method to calculate the variables in Table 1 according to the relevant process to obtain the comprehensive index of DTD.

Explained variable

Green development efficiency (GDE) The increase of GDE relies on the improvement of urban economic development and environmental quality. This is related to the demographic, social, and resource factors involved in the quality of urban development. Therefore, with reference to Zhao et al. (2020), Luo et al. (2022) and Liu et al. (2022a), this study expands the variables from "inputs-desired outputs-undesired outputs" to construct the urban GDE evaluation index system (Table 2).
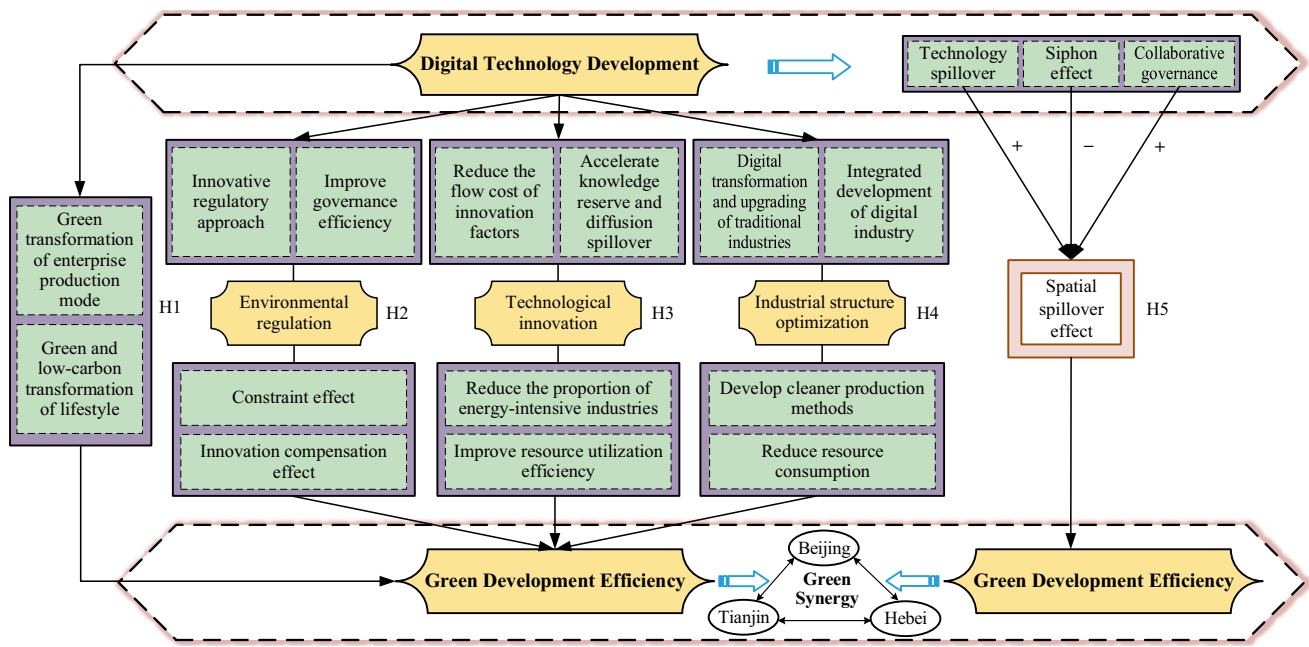
Fig. 1 The mechanism diagram of DTD in urban GDE in the BTH region

The system includes economic, natural, and social dimensions. Compared with Dong et al. (2021), Lyu et al. (2022), Yang and Ni (2022), and Ding et al. (2022), the input aspects add land input and policy inputs. The desired outputs referred to in Yang et al. (2022a) additionally consider environmental benefits and social benefits. The undesired outputs add domestic waste emission indicate negative environmental outputs.

For indicator measurement, Yuan et al. (2022) indicated that the super-SBM model that considers undesired outputs can solve the slackness problem caused by the traditional data envelopment analysis model. It can also solve the problem that the SBM model cannot rank multiple efficiency effective units. Thus, referring to Zhu et al. (2019), this study uses Tone's (2004) modified super-SBM model

to measure urban GDE with the help of the MAXDEA software. Higher GDE values indicate better urban development benefits and vice versa.

Mediating variables

Environmental regulation (ER) The "Porter hypothesis" argued that ER can stimulate firms to invest in environmental technology transformation and obtain "innovation compensation." The "cost constraint theory" argued that ER can increase enterprises' production costs, thus dragging down economic efficiency (Luo et al. 2022). Referring to Song and Han (2022) and Zheng et al. (2023), this study selects industrial SO_2 emissions, industrial smoke (dust) emissions, and industrial wastewater emissions to

Table 1 Digital technology development level evaluation index system

Target layer	Guideline layer	Indicator layer	Measurement variables
Digital Technology Development Index	Digital factor input	Digital industry workforce size	The number of employees in the information transmission, computer services, and software industry accounted for the proportion of employees in urban units
	Digital technology output	Computer service	Total telecom services per capita
	Digital infrastructure	Internet penetration rate	Internet users per 100 people
		Mobile phone penetration rate	Number of mobile phone subscribers per 100 people
	Digital trading development	Digital financial inclusion	Digital inclusive finance index

Table 2 Urban green development efficiency evaluation index system

Indicators	Category	Indicator composition	Instructions
Inputs	Cost inputs	Capital input	Urban fixed asset investment (billion yuan)
		Labor input	Number of employees in urban units at year-end (million people)
		Land input	Urban built-up area (km^2)
		Energy input	Total energy consumption (million t of coal)
		Policy input	Technological and environmental protection expenditures in city budgets (billion yuan)
Outputs	Undesired outputs	Exhaust emission	Industrial sulfur dioxide emissions (million t)
		Wastewater discharge	Industrial wastewater discharge (million t)
		Smoke and dust emission	Industrial fume and dust emissions (million t)
		Garbage consumption	Domestic garbage (million t)
	Desired outputs	Economic benefit	Gross regional product (million yuan)
		Environmental benefit	Greening coverage area (km^2)
		Social benefit	Per capita disposable income of urban residents (million yuan)

form the ER index system. Then, the entropy method is used to calculate the comprehensive ER index.

Technological innovation level (TIL) The increase in TIL is conducive to improving enterprises' technical efficiency of production and management level of the environment, which may promote the improvement of urban GDE. Referring to Zheng et al. (2023), this study uses the ratio of science and technology expenditure to local fiscal expenditure to measure TIL.

Industrial structure optimization (ISO) Industrial structure has a decisive role in the input–output efficiency of resource factors. Therefore, ISO has a significant role in regulating resource consumption and pollution emission (Song et al. 2021). Following Zhu et al. (2019), this study uses the ratio of the added value of the tertiary industry to the added value of the secondary industry to measure ISO.

Control variables

To more accurately analyze the correlation between DTD and urban GDE, this study controls for the following variables. ① Population density (POP) is measured by the number of people per unit of land area in the city (Yuan et al. 2022). ② Government intervention degree (GID) is measured by the proportion of total fiscal expenditure in GDP (Luo et al. 2022). ③ Capital labor rate (CLR) is expressed by the ratio of the urban annual fixed asset investment to employment (Liu et al. 2022b). ④ Environmental preference (EP) is described by the urban green coverage (Yuan et al. 2022). ⑤ Infrastructure level (INF) is expressed by the urban road area per capita at year end (Gao et al. 2022). All the variables are logarithmically

processed before empirical estimation to eliminate heteroskedasticity in the model.

Model construction

Fixed-effects model

To reasonably examine the effect of DTD on urban GDE, this study selects the panel model type by correlation test. According to the Hausman test, the value of the statistic is 35.78, which passes the 1% significance test. The result supports to adopt the fixed effect model. Therefore, model (1) is constructed to verify the direct impact of DTD on GDE:

$$\ln GDE_{it} = \alpha_0 + \alpha_1 \ln DTD_{it} + \alpha_2 \ln POP_{it} + \alpha_3 \ln GID_{it} \\ + \alpha_4 \ln CLR_{it} + \alpha_5 \ln EP_{it} + \alpha_6 \ln INF_{it} + u_i + v_t + \varepsilon_{it} \quad (1)$$

where GDE_{it} is the GDE in period t of city i and DTD_{it} is the DTD level in period t of city i. $\boldsymbol{u_i}$ is the unobserved individual fixed effect, v_t is the control time fixed effect, and ε_{it} is the random disturbance term.

Mediating effect model

Models (2) and (3) are used to test the role of environmental regulation, technological innovation level, and industrial structure optimization in the path of DTD affecting urban GDE:

$$\ln ESI_{it} = \beta_0 + \beta_1 \ln DTD_{it} + \beta_2 \ln POP_{it} + \beta_3 \ln GID_{it} \\ + \beta_4 \ln CLR_{it} + \beta_5 \ln EP_{it} + \beta_6 \ln INF_{it} + u_i + v_t + \varepsilon_{it} \quad (2)$$

$$\ln GDE_{it} = \varphi_0 + \varphi_1 \ln DTD_{it} + \varphi_2 \ln ESI_{it} + \varphi_3 \ln POP_{it} + \varphi_4 \ln GID_{it} \\ + \varphi_5 \ln CLR_{it} + \varphi_6 \ln EP_{it} + \varphi_7 \ln INF_{it} + u_i + v_t + \varepsilon_{it} \quad (3)$$

where ESI_{it} represents the mediating variables, which are ER, TIL, and ISO in period t in city i. $\beta 1 \times \varphi 2$ is the mediating effect indicating DTD's indirect impact on urban GDE through ER, TIL, and ISO.

Spatial Durbin model (SDM)

Since urban DTD has spatial network characteristics such as mobility and replicability, it may have spatial spillover effects. The green development level of a local city will impact neighboring cities, and there may also be a correlation in space. To explore the spatial spillover effect of DTD on urban GDE in the BTH region, the SDM is constructed by adding a spatial interaction term in model (4):

$$\ln GDE_{it} = \lambda_0 + \rho W \ln GDE_{it} + \lambda_1 \ln DTD_{it}$$
$$+ \varphi_1 W \ln DTD_{it} + \lambda_2 X_{it} + \varphi_2 WX_{it} + u_i + v_t + \varepsilon_{it} \quad (4)$$

where ρ is the spatial autocorrelation coefficient. W is the spatial weight matrix. X_{it} is the control variables. φ_1 and φ_2 are the coefficients of independent and control variables' spatial interaction terms, respectively. Considering the high economic closeness of cities in the BTH region, W used the economic geographic weight matrix to measure the spatial correlation of DTD between cities. Formula (5) is as follows:

$$W_{i,j} = \begin{cases} \frac{GDP_i \times GDP_j}{d_{i,j}^2}, i \neq j \\ 0, i = i \end{cases} \quad (5)$$

where GDP_i and GDP_j represent the GDP of the city i and j, respectively. d_{ij} represents the geographic distance between city i and city j.

We considered that Lesage and Pace (2009) indicated that the regression coefficient of DTD in the SDM model failed to reflect its marginal effect on urban GDE.

Therefore, referring to the process of Ding et al. (2022) and Liu et al. (2022b), this study decomposes the direct, indirect, and total effects of DTD on urban GDE using the SDM partial differential method, which will investigate the spatial spillover effects in more detail.

Data description and descriptive statistics

This study uses 13 cities in the BTH region from 2011 to 2019 as the research samples. The panel data of each city are obtained from the China Statistical Yearbook, China Urban Statistical Yearbook, China Environmental Statistical Yearbook, and statistical bulletins from 2011 to 2019. Furthermore, the missing data are supplemented by the interpolation method. The results of descriptive statistics for each variable are shown in Table 3.

Empirical analyses

Benchmark regression results

The regression results of model (1) are shown in Table 4. The regression results show adjusted $R^2 > 0.5$ in all cases, indicating that the model has a high fit. The coefficient values of $lnDTD$ in columns (1) and (2) are 0.242 and 0.316, and both are significant at the 1% level regardless of whether control variables are included. It indicates that DTD significantly enhances the urban GDE in the BTH region. Specifically, for every 1% increase in DTD, urban GDE will improve by 0.316%, which confirms hypothesis 1. The possible explanation is that the wide application of digital technology within various fields in the BTH region made the production process efficient and low carbon, forming a green development model with low energy consumption and high output. Furthermore, the construction of a "smart

Table 3 Descriptive statistics of variables

Variables	Explanations	Average	St.d	Min	Max
GDE	Green development efficiency	0.752	0.127	0.514	1.039
DTD	Digital technology development	0.103	0.0601	0.0328	0.376
ER	Environmental regulation	0.109	0.127	6.30e–05	0.815
TIL	Technological innovation level	11,526	25,191	165	131,716
ISO	Industrial structure optimization	1.205	0.883	0.516	5.169
POP	Population density	3339	2115	690	8461
GID	Government intervention degree	0.182	0.0567	0.0812	0.394
CLR	Capital labor rate	41.49	18.85	8.531	92.13
EP	Environmental preferences	42.63	7.242	29.28	92.87
INF	Infrastructure level	16.79	3.593	5.260	27.95

Table 4 The regression results of direct effect and explanatory variable on mediating variables

Variables	(1) lnGDE	(2) lnGDE	(3) lnER	(4) lnTIL	(5) lnISO
lnDTD	0.242*** (11.38)	0.316*** (13.34)	−1.986*** (−6.50)	2.706*** (16.84)	0.648*** (15.07)
lnPOP		−0.024* (-1.59)	0.249 (1.27)	0.599** (5.79)	0.099*** (3.58)
lnGID		−0.224*** (−7.09)	0.216 (0.53)	−1.079*** (−5.04)	0.420*** (7.35)
lnCLR		−0.026 (−1.08)	0.831*** (2.72)	−0.811*** (-5.04)	−0.153*** (-3.55)
lnEP		0.202*** (−2.93)	1.663* (1.88)	−1.332*** (−2.86)	0.456*** (3.66)
lnINF		0.017 (0.32)	1.889*** (2.80)	−0.342 (−0.96)	−0.333*** (−3.50)
Constant	0.282*** (5.42)	1.061*** (3.38)	−24.015*** (−5.93)	16.758*** (7.87)	1.310** (2.30)
Year	Yes	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes	Yes
Adjust R^2	0.530	0.688	0.601	0.821	0.892

*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$

city" through digital technology improved the quality of regional environmental governance, ultimately realizing the improvement of urban GDE in the BTH region.

For the control variables, the coefficient of *lnPOP* and *lnGID* are −0.024 and −0.224, which are significant at the 10 and 1% levels, respectively. They indicate that population size and government intervention suppress urban GDE. The reason may be that the BTH region failed to convert population size into human capital benefits during the development process. The "negative effects" caused by overpopulation such as air pollution and resource and environmental constraints are detrimental to urban green growth. Moreover, the stronger the government intervention in the BTH region, the more local governments tend to adopt administrative environmental regulations for pollution reduction. It creates resource distortion and is not conducive to improving urban GDE. The coefficient of *lnEP* is 0.202 at the 1% significance level, indicating that environmental preferences contribute to improving urban GDE. Cities with stronger environmental preferences in the BTH region usually focus on ecological and environmental management. They actively guide enterprises to make a green and high-quality transformation, thus obtaining higher urban GDE.

Transmission mechanism analysis

Referring to the mediation effect test procedure of Ding et al. (2022), Lee et al. (2022), and Luo et al. (2022), this part uses a stepwise test method to validate models (2) and (3). To further ensure the robustness of the mediating test results, this study uses the Bootstrap test to strengthen the verification of the mediating effect. The regression results of the explanatory variable on mediating variables are shown in Table 4. The coefficient of *lnDTD* in column (3) is −1.986, with significance at the 1% level. Since ER is measured by three waste emissions,

Table 5 Regression results of DTD on urban GDE through ER, TIL, and ISO

Variables	(1) lnGDE	(2) lnGDE	(3) lnGDE
lnDTD	0.277*** (10.22)	0.162*** (3.90)	0.344*** (8.27)
lnER	−0.020*** (−2.76)		
lnTIL		0.057*** (4.36)	
lnISO			−0.043** (−0.81)
lnPOP	−0.019 (−1.30)	−0.058*** (-−.62)	−0.020 (−1.25)
lnGID	−0.219*** (−7.15)	−0.162*** (−5.00)	−0.206*** (−5.33)
lnCLR	−0.009 (−0.38)	0.021 (0.84)	−0.032 (−1.28)
lnEP	−0.169** (−2.48)	−0.126* (−1.90)	−0.182** (−2.50)
lnINF	0.054 (1.03)	0.036 (0.74)	−0.029 (−0.58)
Constant	0.584* (1.67)	1.064*** (2.92)	1.116*** (3.46)
Year	Yes	Yes	Yes
City	Yes	Yes	Yes
Adjust R^2	0.709	0.735	0.690

*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$

its smaller value indicates the higher intensity of ER, which is a negative indicator. Therefore, it indicates that DTD significantly improves the intensity of ER in the BTH region. The coefficient of *lnDTD* in columns (4) and (5) is 2.706 and 0.648, and both are significant at the 1% level. It indicates that DTD has obviously contributed to the TIL and ISO in the BTH region. The possible explanations are as follows. First, since the collaborative development of the BTH region, cities have focused on environmental governance and leveraged digital technology to build a "smart city," which improved the intensity of ER. Second, the BTH region has abundant digital resources and excellent infrastructure conditions for using digital technology to improve urban TIL. Furthermore, the BTH region has achieved deep integration with the industrial sector using digital technologies, thus promoting the ISO of traditional industries.

The regression results of the explanatory variable on the explained variable after adding the mediating variables are shown in Table 5. Overall, the inclusion of mediating variables does not affect the promotion effect of DTD on urban GDE. The coefficient of *lnER* in column (1) is −0.020, which is significant at the 1% level. However, ER is an inverse indicator. It means that ER significantly increases urban GDE, which confirms hypothesis 3. The above study shows that the "technology spillover effect" of environmental regulation offsets and exceeds the "cost constraint effect" in the BTH region, which is consistent with Porter's hypothesis. In reality, the ER in the BTH region improved the environmental requirements for industrial development. In summary, ER effectively reduced the emission of pollutants and improved the urban GDE in the BTH region.

In column (2), the coefficient of *lnTIL* is 0.057, which is significant at the 1% level, indicating that the level of technological innovation promotes the urban GDE of the BTH region. It indicates that the DTD in the BTH region increases urban GDE by enhancing the TIL, so hypothesis 4 is confirmed. Driven by digital technology, the technological advances in the BTH region help improve the efficiency of environmental management. It changes the previous development style of high energy consumption, high pollution, and low technology, and then promotes high-quality green development in the BTH region.

In column (3), the coefficient of *lnISO* is −0.043, which is significant at the 5% level, indicating that ISO inhibits urban GDE in the BTH region. Specifically, $\beta_1 \times \varphi_2 = 0.648 \times (-0.043) = -0.028$; however, $\varphi_1 = 0.344$, and the two values have different signs. The total effect of DTD on urban GDE (α_1: 0.316) is smaller than the direct effect (φ_1: 0.344). Therefore, the indirect effect of ISO shows a "masking effect." Next, this part further uses the Bootstrap test to verify the "masking effect" of ISO. The results show that the indirect effect of DTD on urban GDE through ISO is −0.028, with a 95% confidence interval [LLCI = −0.186, ULCI = −0.051], excluding 0. Therefore, the "masking effect" of ISO is further confirmed, and hypothesis 5 is not supported. The reason may be that due to the different development orientations of the three cities in the BTH region, there are obvious gradient differences and imbalances in their industrial structure, which makes ISO negatively affect the urban GDE in the BTH region. Especially, Hebei faced a tough period of industrial restructuring and environmental governance due to its rough industrial structure, and its economic growth rate slowed down. Similarly, through the Bootstrap test, the indirect effects of ER and TIL are 0.039 and 0.154, which are significant at the 5 and 1% levels, respectively. Their 95% confidence intervals
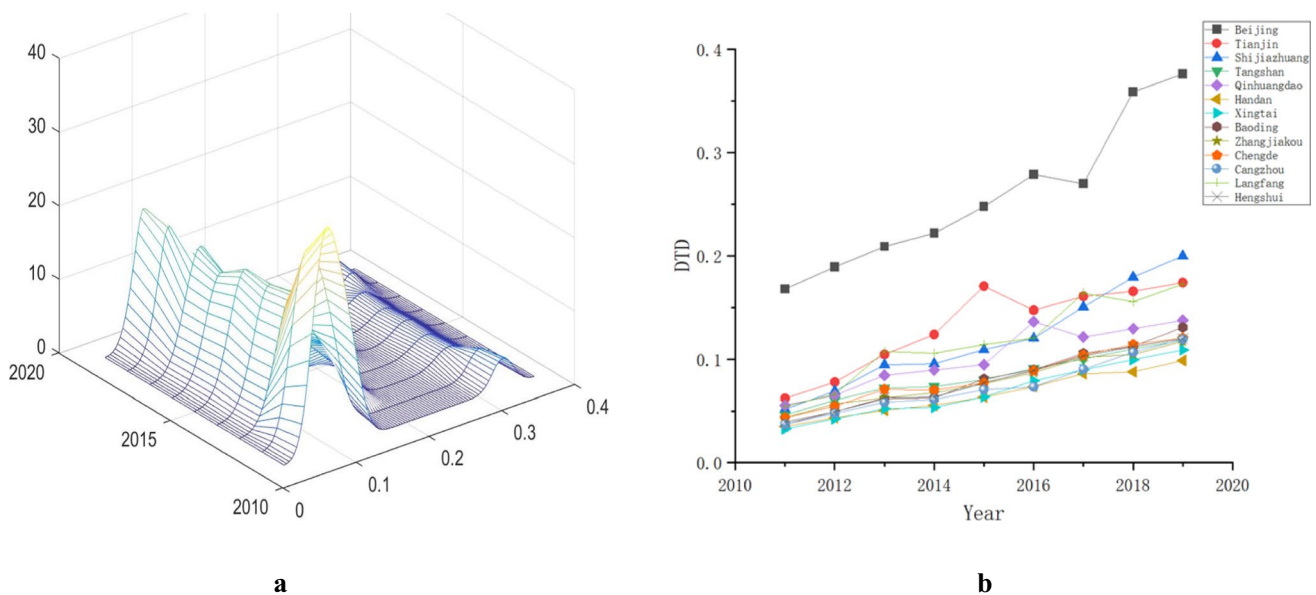
a

b

Fig. 2 **a** Kernel density figure. **b** Time trend figure

are LLCI = 0.007 and ULCI = 0.072 and LLCI = 0.082 and ULCI = 0.226; neither of which excludes 0. Thus, the mediating effects of ER and TIL are further confirmed.

Spatiotemporal evolutionary characteristics and spatial spillover effects

Spatiotemporal evolutionary characteristics

As a nonparametric estimation method, kernel density estimation can describe the distribution conditions of research objects and is specifically described in Zheng et al. (2023). Then, this part uses Matlab16 to plot the kernel density figure (Fig. 2a) to explore the evolution trend of urban DTD. From Fig. 2a, the wave crest of the DTD index for each year is roughly around 0.1 during 2011–2019. Meanwhile, the DTD index shows a trailing trend, indicating the presence of cities with higher DTD levels in the BTH region. Combined with the time trend figure (Fig. 2b), the DTD level of the BTH region shows an overall upward trend, but Beijing, Tianjin, and Shijiazhuang are further away from other cities. This is due to their strengths in economic development and technological innovation, which are favorable to enhancing higher levels of urban DTD.
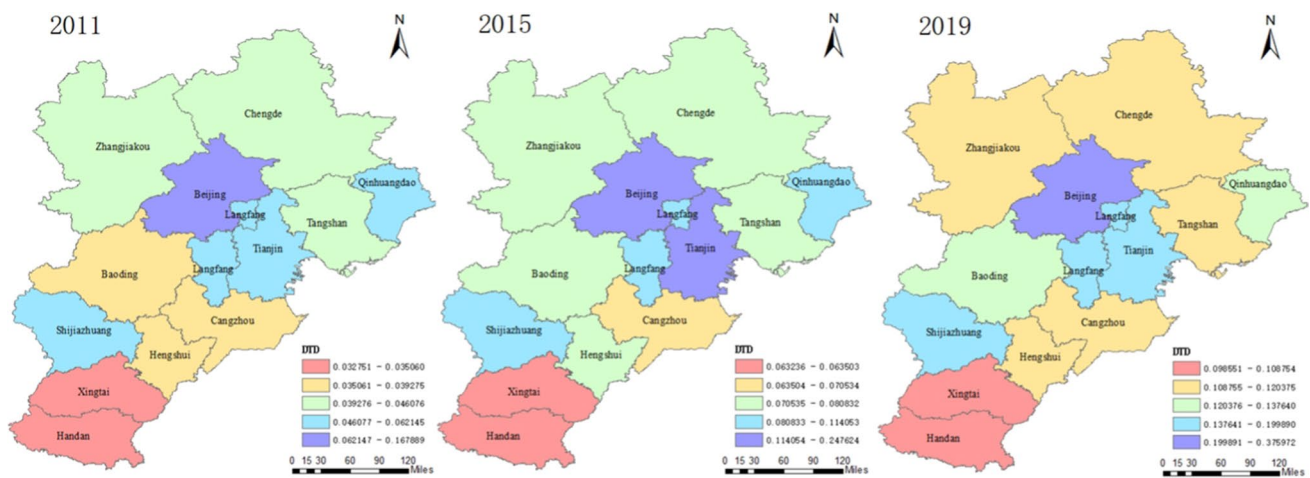

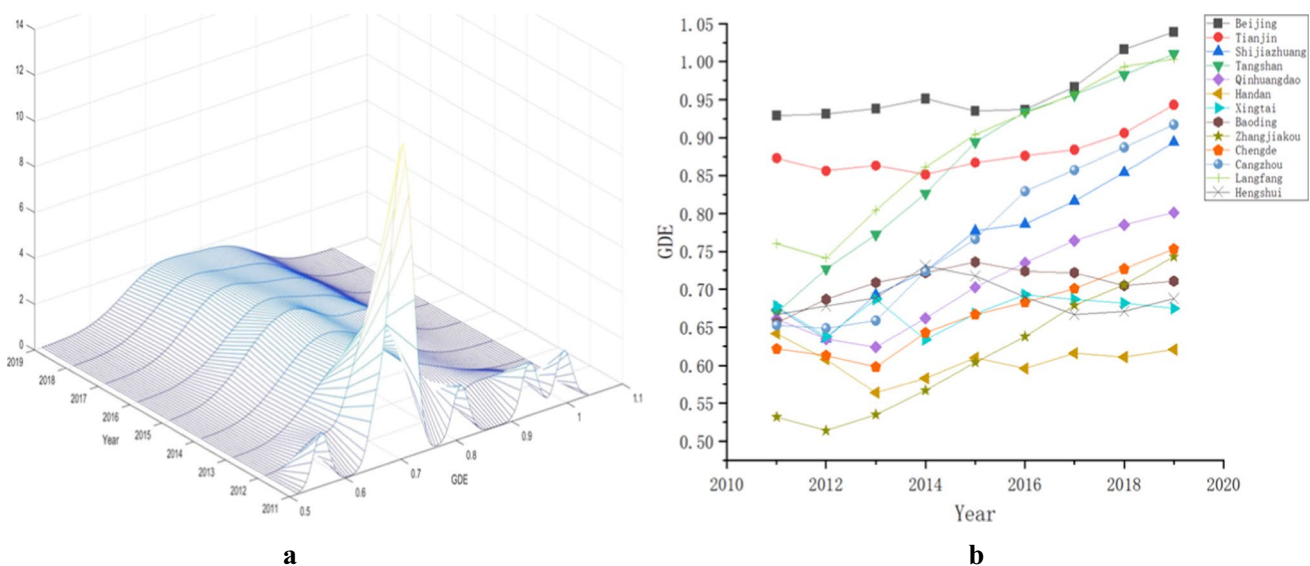**Fig. 3** Spatial distribution of urban DTD levels

a

b

Fig. 4 **a** Kernel density figure. **b** Time trend figure

Then, this part draws the spatial distribution figure (Fig. 3) by using the ArcGIS 10.7 software to visualize the geographical distribution of urban DTD in the BTH region. Overall, the urban DTD faces the problem of unbalanced development. It reflects in the fact that Beijing's DTD level is always the highest, and that the DTD level of neighboring cities such as Langfang increases rapidly. Furthermore, Tianjin and Shijiazhuang also consistently maintain high DTD levels. However, southeastern cities such as Handan, Xingtai, Hengshui, and Cangzhou are long-lagging behind in DTD levels. Therefore, it is still an urgent task to narrow the urban DTD gap in the BTH region to avoid the expansion of the "digital divide."

Similarly, from the kernel density figure (Fig. 4a), the height of the wave crest gradually decreases, and the width subsequently increases, indicating that the differences in urban GDE are becoming more significant. From the time trend figure (Fig. 4b), the urban GDE in the BTH region overall showed a fluctuating upward trend, and the mean value of urban GDE increased from 0.694 in 2011 to 0.831 in 2019. The urban GDE in the BTH region can be roughly divided into the "oscillation period" (2011–2014) and the "rising period" (2015–2019). The early rough growth model of the BTH region caused the growth of urban GDE to fluctuate. With the improvement of regional environmental awareness and sustainable development requirements, cities relied on green transformation and technological innovation to drive the GDE to steadily increase.

From the spatial distribution figure (Fig. 5), the urban GDE shows a "ladder" characteristic, with apparent high and low partitions. In 2011, only Beijing and Tianjin are highly efficient cities, and most Hebei cities are low efficiency. By 2019, the urban GDE of Tangshan and Langfang had significantly improved, while Xingtai and Handan had dropped to inefficient levels. The growth rate of urban GDE in the northeast part of the BTH region is faster than that in the southwest

region. It shows a trend of spreading from the center to the surrounding areas. Furthermore, the "agglomeration" differentiation of cities is obvious. It has formed high-efficiency areas centered in Beijing, Tianjin, and Langfang, and inefficient areas mainly in Handan, Xingtai, and Hengshui.

Spatial correlation test

Before exploring the spatial effect of DTD on urban GDE, it is necessary to test whether DTD is spatially correlated. This study uses global Moran's I to test whether the DTD in the BTH region has spatial autocorrelation on a global scale. It reflects the overall characteristics of the spatial correlation of urban DTD. The expression is as follows:

$$Moran's I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\left(\sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij}\right) \sum_{i=1}^{n} (y - \bar{y})^2} \tag{6}$$

Here, n is the total number of spatial units. y_i is the DTD level of spatial unit i. ω_{ij} is the spatial weight matrix coefficient. Moran's $I \in [-1,1]$, which measures the overall correlation of spatial unit elements. Moran's $I > 0$ means positive correlation, Moran's $I < 0$ means negative correlation, and Moran's $I = 0$ means no correlation.

To more visually display the relative geographic distribution of urban DTD, this study plots the global Moran's I scatter figure (Fig. 6). The global Moran's I value of *lnDTD* is 0.614 and passes the 1% significance test, which indicates that urban DTD has a significant positive correlation in space. Except for Beijing and Tianjin, the distribution of DTD in most cities is concentrated in the first and third quadrants, showing obvious H–H and L-L clustering. Furthermore, the DTD levels of 13 cities in
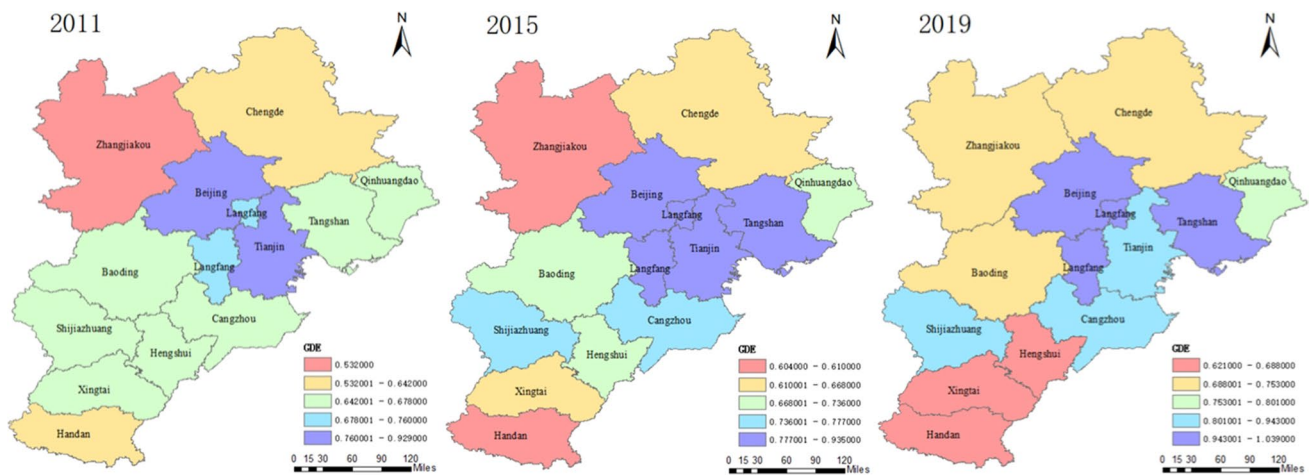

Fig. 5 Spatial distribution of urban GDE

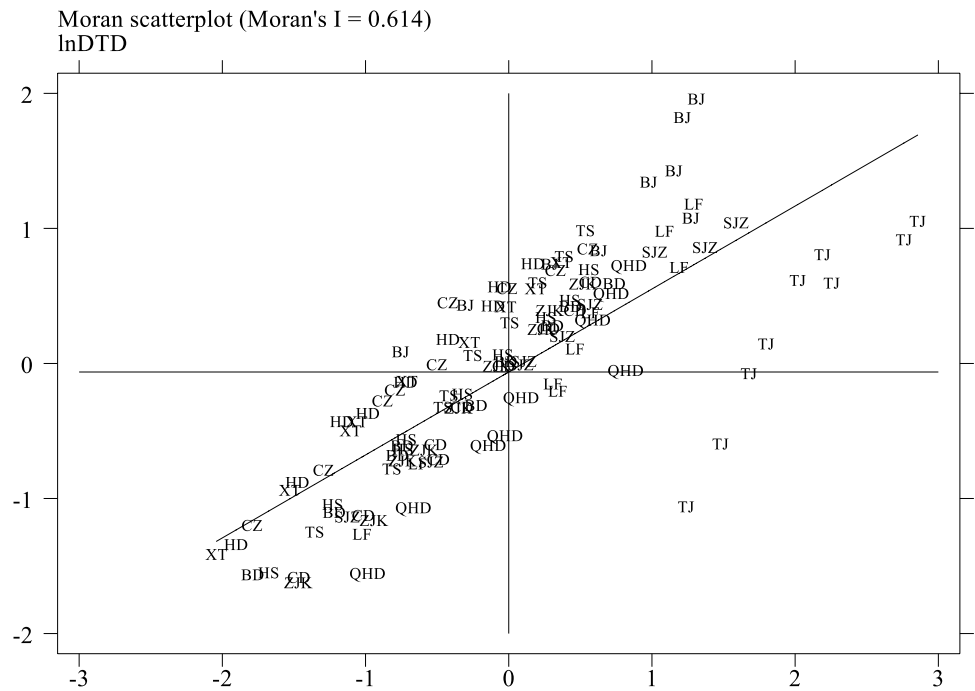**Fig. 6** Moran's I scatter plot for urban DTD

Moran scatterplot (Moran's I = 0.614)
lnDTD

Table 6 Spatial econometric model tests

Inspection content	Test method	Statistical values	*P*-value
SEM and SAR model test	LM-error	17.049	0.000
	Robust LM-error	11.571	0.001
	LM-lag	9.357	0.002
	Robust LM-lag	19.971	0.000
Simplified test of SDM	LR-SDM-SAR	65.26	0.000
	LR-SDM-SER	58.10	0.000

the BTH region have jumped to different degrees. Tianjin shifted from the fourth quadrant to the first quadrant, and the other cities mostly shifted from the third quadrant to the first quadrant. It also shows a positive correlation, indicating that the DTD in the BTH region jumped from generally lower levels to higher levels during 2011–2019. In summary, urban DTD has a significant positive spillover effect, and it is necessary to use a spatial regression model for empirical analysis.

Table 7 Spatial Durbin model regression results

Variables	(1) lnGDE	(2) Spatial lag term lnGDE	(3) Direct effect lnGDE	(4) Indirect effect lnGDE	(5) Total effect lnGDE
lnDTD	0.120** (2.31)	0.687*** (6.80)	0.107** (2.15)	0.644*** (5.39)	0.751*** (7.66)
lnPOP	0.006 (0.39)	0.199*** (3.84)	0.002 (0.09)	0.179*** (3.75)	0.181*** (3.23)
lnGID	−0.179*** (−6.95)	−0.118 (−1.14)	−0.175*** (−6.37)	−0.113 (−1.12)	−0.288*** (−2.84)
lnCLR	−0.076*** (−2.60)	−0.052 (−0.75)	−0.073** (−2.29)	−0.039 (−0.59)	−0.111 (−1.48)
lnEP	0.221*** (3.31)	0.647*** (3.66)	0.222*** (3.07)	0.614*** (3.29)	0.836*** (3.65)
lnINF	0.071* (1.77)	0.276** (2.35)	0.067* (1.65)	0.256** (2.04)	0.327** (2.26)
Spatial rho	−0.087* (−0.53)				
Variance sigma2-e	0.004*** (7.80)				
Adjust R^2	0.593				

*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$

Spatial spillover effect

This study conducted LR and LM tests to select the appropriate spatial econometric model (Table 6). The LM test results show that LM-lag, robust LM-lag, LM-error, and robust LM-error are significant at the 1% level. It indicates that compared with the spatial auto-regressive model (SAR), the spatial error model (SEM) is more appropriate. The LR test results show that SDM cannot be degraded to the SEM or SAR model. Combined with the Hausman test, the results show that using the fixed-effects model is better than using the random-effects model. Therefore, this study uses SDM with fixed effects to test the spatial spillover effect.

Similar to Fan et al. (2022), this study decomposes the effect of DTD on urban GDE into direct, indirect, and total effects (Table 7). The coefficient of *lnDTD* in column (1) is 0.120 and significant at the 5% level, indicating that DTD improves the local urban GDE in the BTH region. The spatial lag term of *lnDTD* in column (2) is 0.687 and significant at the 1% level, indicating that the local DTD has a positive spillover effect on the GDE of neighboring cities in the BTH region. The coefficients of *lnDTD* in columns (3), (4), and (5) are significantly positive at the 5 and 1% levels, which indicates that DTD positively affects the GDE in both local city and neighboring cities in the BTH region. Specifically, the coefficient of *lnDTD* in column (4) is larger than that in column (3), which confirms that urban DTD has a strong spatial spillover effect on the BTH region. The possible explanation is that the increased level of local DTD improves green production technology through the technology spillover effect. Thus, it positively affects the

local urban GDE in the BTH region. Meanwhile, neighboring cities can imitate or absorb high-level technology and production experience at a lower cost, and local DTD has a "diffusion effect" on neighboring cities. Therefore, local DTD can promote the improvement of GDE in neighboring cities of the BTH region.

For the control variables, the spatial lag term of *lnPOP* in column (2) is significantly positive at the 1% level, indicating that POP can raise the GDE of neighboring cities in the BTH region. Fang et al. (2020) showed that over-concentration of population inhibits urban GDE. Local cities share a large amount of population migration from neighboring cities, which will increase the GDE of neighboring cities. The coefficients of *lnGID* and *lnLCR* are significantly negative at the 1% level in column (1) and not significant in column (2). It indicates that GID and LCR suppress local urban GDE and that the suppression effect is regional with no spatial spillover in the BTH region. The possible reason is that with the increase of GID, the BTH governments tend to use stricter administrative environmental regulations to constrain social production and development. Due to resource misallocation and green transition, the productivity of enterprises fluctuates in the short term, which is not conducive to improving urban GDE. The relatively small correlation coefficients show that little green benefits are obtained in the short term from fixed asset investments in the BTH region. The coefficients of *lnEP* and *lnINF* are significantly positive at the 1 and 10% levels in column (1), and the spatial lag term in column (2) is significantly positive at the 1 and 5% levels. It indicates that EP and INF raise the GDE of both local city and neighboring cities in the BTH region. With stronger

Table 8 Robustness test: SDM regression results

Variables	(1) lnGDE	(2) Spatial lag term lnGDE	(3) Direct effect lnGDE	(4) Indirect effect lnGDE	(5) Total effect lnGDE
lnDTD	0.451***	1.580***	0.395***	0.977***	1.372***
	(12.94)	(6.37)	(9.28)	(3.79)	(4.81)
lnPOP	0.039***	0.341***	0.024*	0.224***	0.248***
	(2.70)	(4.44)	(1.83)	(3.68)	(3.62)
lnGID	−0.367***	−1.793***	−0.297***	−1.161***	−1.458***
	(−11.90)	(−8.21)	(−7.98)	(−4.57)	(−5.21)
lnCLR	−0.051*	−0.600***	−0.025	−0.409***	−0.433***
	(−1.90)	(−4.12)	(−0.94)	(−3.44)	(−3.30)
lnEP	0.110**	0.443	0.102*	0.301	0.403
	(1.97)	(1.16)	(1.80)	(1.02)	(1.29)
lnINF	0.076	1.042***	0.034	0.736***	0.770***
	(1.63)	(3.83)	(0.69)	(2.92)	(2.71)
Spatial rho	−0.488*				
	(−1.92)				
Variance sigma2-e	0.004***				
	(7.95)				
Adjust R²	0.551				

*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$

environmental preferences in the BTH region, cities have cooperated in environmental management and developed a green economy that has reaped effective benefits. Furthermore, the increase in infrastructure level has achieved regional connectivity, thus promoting regional green synergistic development in the BTH region.

Robustness tests

Replacement space weight matrix

This part uses the inverse geographic distance matrix to verify the spatial spillover effect of DTD on urban GDE. The regression results of the SDM are shown in Table 8. Except for the significant reduction of EP and INF, the signs of regression coefficients of other variables are consistent with the above studies. Only the size and significance of the values are relatively improved, which shows that DTD still has a significant spillover effect on urban GDE in the BTH region. This confirms the robustness of the above empirical results.

Endogeneity test

Considering the possible reverse causality between urban GDE and DTD, this study uses an instrumental variable method to alleviate the endogeneity problem. Referring to Bartik (2009), this study constructs an instrumental variable "Bartik instrument," that is, the interaction term ($lnDTD_{i,t-1} \times \Delta lnDTD_{t,t-1}$) of the lagged one-period term ($lnDTD_{i,t-1}$) and the first-order difference term ($\Delta lnDTD_{t,t-1}$). The reasons are as follows: first, the lag period of the DTD index is significantly correlated with urban GDE, so there is no weak instrumental variable; second, the interference term of the current period cannot affect the result of the lag period of the DTD index, which satisfies the exogenous constraint. Based on this instrumental variable, the two-stage least squares method (IV-2SLS) is used for estimation. The model is as follows:

$$lnDTD_{it} = \beta_0 + \beta_1 lnIV_{it} + \beta_2 lnPOP_{it} + \beta_3 lnGID_{it} + \beta_4 lnCLR_{it}$$
$$+ \beta_5 lnEP_{it} + \beta_6 lnINF_{it} + u_i + v_t + \varepsilon_{it} \tag{7}$$

$$lnGDE_{it} = \beta'_0 + \beta'_1 lnDTD_{it} + \beta'_2 lnPOP_{it} + \beta'_3 lnGID_{it}$$
$$+ \beta'_4 lnCLR_{it} + \beta'_5 lnEP_{it} + \beta'_6 lnINF_{it} + u_i + v_t + \varepsilon_{it} \tag{8}$$

As shown in Table 9, the coefficients of instrumental variables in the first-stage regression results are significantly positive. The unidentifiable test (Kleibergen–Paap rk LM test) is significant at the 1% level. For the weak instrumental variable test, the Kleibergen–Paap Wald rk F statistic is higher than 16.38 (the critical value at the 10% level of stock Yogo weak identification test). The above test

Table 9 Robustness test: IV-2SLS regression results

Variables	Phase 1 lnDTD	Phase 2 lnGDE
$lnDTD_{i,t-1}*\Delta lnDTD_{t,t-1}$	0.405*** (3.05)	
lnDTD		0.453*** (4.98)
Controls	Yes	Yes
Year	Yes	Yes
City	Yes	Yes
Constant	−2.549** (−2.13)	1.492*** (3.41)
Adjust R^2		0.667
N	104	104
Kleibergen–Paap rk LM statistic	7.561 [0.006]	
Kleibergen–Paap Wald rk F statistic	19.93 {16.38}	

() is the standard error value, [] is the p value, and {} is the critical value at the 10% level of the stock Yogo weak identification test. *** $p < 0.01$ and ** $p < 0.05$

proves the selection of the instrumental variable is reasonable. After considering the endogeneity, the coefficient of *lnDTD* is still positive, and the regression results in the second stage pass the significance test at the 1% level. It also shows that DTD can improve urban the GDE in the BTH region, which confirms the robustness of the previous regression results.

Conclusions and recommendations

In the critical period of China's economic digitalization and green development, how to use digital technology to promote urban green development has become the focus of practice and academia. In this context, based on the panel data of 13 cities in the BTH region from 2011 to 2019, this study examines the effects and mechanisms of DTD on urban GDE with multi-dimensional by using the fixed effect model, mediation effect model, and spatial Durbin model. This study provides a strong empirical basis for Chinese regions to exert the driving effect of digital tools on urban green development.

The following interesting and noteworthy findings can be identified from the empirical analysis.

(1). Unlike the conclusion of Asongu et al. (2018), the results confirm that DTD is conducive to improving urban GDE in the BTH region.

(2). The mediating effect test shows that DTD increases urban GDE by improving environmental regulation

intensity and technological innovation level. Interestingly, the industrial structure optimization shows a "masking effect." This is different from Zhu et al. (2019), which concludes that industrial structure adjustment can improve GDE.

(3). The DTD is generally on an upward trend in the BTH region, but there is a "digital divide" between cities. The urban GDE shows a fluctuating upward trend, which can be divided into "shock period" and "rising period." The geographical distribution shows a "ladder" characteristic, with obvious high-low partitions.

(4). The DTD shows a positive spatial autocorrelation in the BTH region, exhibiting a spatial distribution pattern of "H–H" and "L-L" clustering. The DTD has a positive spatial spillover effect on urban GDE in the BTH region. It indicates that DTD promotes the GDE of neighboring cities.

Around the above conclusions, this study proposes the following recommendations.

(1). The BTH region should increase the construction of digital infrastructures such as 5G and artificial intelligence. Meanwhile, the BTH region should fully utilize digital technology to empower the green transformation for key emission and carbon reduction fields in life services, transportation, and industrial manufacturing. By using digital technology to optimize production processes and resource allocation efficiency, it is possible to increase productivity while reducing environmental pollution. In this way, the urban GDE can be improved. This can provide a Chinese paradigm for the new pattern of global green development.

(2). ① In terms of environmental regulation, the BTH region can use digital technology to innovate intelligent environmental regulation manners. It can help the government to propose targeted environmental management strategies. Moreover, the BTH region needs to improve the digital government platform and environmental management information system. This will facilitate the government to formulate dynamic urban green development policies according to social needs. ② In terms of technological innovation, the BTH region should use digital technology to promote green technological innovation. Through clean technology innovation, enterprises can develop green and low-carbon production methods. Furthermore, the BTH region can build a collaborative innovation platform to acquire, integrate, and share innovation resources. It can help enterprises innovate production technology through resource restructuring,

thus increasing productivity. ③ In terms of industrial structure optimization, the BTH region should vigorously develop high-tech industries with low energy consumption and high added value spawned by digital technology. Meanwhile, the BTH region needs to deepen the intelligent use of digital technology in manufacturing to improve the energy use efficiency and environmental management level of traditional industries. This will help the traditional industry develop a green manufacturing mode and boost the green development of the city.

(3). Due to the differences in digital resources and green development among cities, the BTH region should properly plan the progress and patterns of DTD and green development among cities. Beijing and Tianjin should exert the radiation-driving effect of DTD and increase the spillover effect of their knowledge and technology to neighboring cities. Meanwhile, the BTH government should formulate favorable tax concessions and fiscal expenditure policies to support the DTD and green development in relatively backward cities. This will promote the synergistic development of digitalization and greening in the BTH region.

Nevertheless, there is still the following space to be filled. First, the multi-layer measurement system of DTD under the Chinese background still needs to be refined and supplemented. Second, this study mainly controls the variables at the city level and lacks discussion on the control variables of financial development and foreign trade. Furthermore, this study only briefly analyzes the spatial evolution of DTD and GDE in the BTH region. On this basis, subsequent research can focus on analyzing their spatial logical relationship and other impact mechanisms.

Author contribution Yangyang Yang: conceptualization, methodology, formal analysis, data acquisition, visualization, validation, and writing (original draft preparation and reviewing and editing). Runde Gu: formal analysis, data acquisition, validation, writing (reviewing and editing), and funding acquisition. Shengbin Ma: data Acquisition, visualization, and writing (original draft preparation). Weike Chen: conceptualization, methodology, formal analysis, writing (reviewing and editing), supervision, and funding acquisition.

Data availability Available upon request by contacting the author.

Declarations

Conflict of interest The authors declare no competing interests.

References

Asongu SA, Roux SL, Biekpe N (2018) Enhancing ICT for environmental sustainability in sub-Saharan Africa. Technol Forecast Soc 127:209–216. https://doi.org/10.1016/j.techfore.2017.09.022

Bartik T (2009) How do the effects of local growth on employment rates vary with initial labor market conditions? Upjohn Institute Working Paper No. 09–148. https://doi.org/10.2139/ssrn.1372814

Cardona M, Kretschmer T, Strobel T (2013) ICT and productivity: conclusions from the empirical literature. Inf Econ Policy 25(3):109–125. https://doi.org/10.1016/j.infoecopol.2012.12.002

Chen WT, Yan WT (2020) Impact of internet electronic commerce on SO_2 pollution: evidence from China. Environ Sci Pollut Res 27:25801–25812. https://doi.org/10.1007/s11356-020-09027-1

Ding J, Liu BL, Shao XF (2022) Spatial effects of industrial synergistic agglomeration and regional green development efficiency: evidence from China. Energ Econ 112:106156. https://doi.org/10.1016/j.eneco.2022.106156

Dong F, Li YF, Qin C, Sun JJ (2021) How industrial convergence affects regional green development efficiency: a spatial conditional process analysis. J Environ Manage 300:113738. https://doi.org/10.1016/j.jenvman.2021.113738

Fan M, Yang P, Li Q (2022) Impact of environmental regulation on green total factor productivity: a new perspective of green technological innovation. Environ Sci Pollut Res 29:53785–53800. https://doi.org/10.1007/s11356-022-19576-2

Fang GC, Wang QL, Tian LX (2020) Green development of Yangtze River Delta in China under Population-Resources-Environment-Development-Satisfaction perspective. Sci Total Environ 727:138710. https://doi.org/10.1016/j.scitotenv.2020.138710

Gao D, Li G, Yu JY (2022) Does digitization improve green total factor energy efficiency? Evidence from Chinese 213 cities. Energy 247:123395. https://doi.org/10.1016/j.energy.2022.123395

Gu RD, Li CF, Li DD, Yang YY, Gu S (2022) The impact of rationalization and upgrading of industrial structure on carbon emissions in the Beijing-Tianjin-Hebei urban agglomeration. Int J Environ Res Public Health 19:7997. https://doi.org/10.3390/ijerph19137997

Huber J (2000) Towards industrial ecology: sustainable development as a concept of ecological modernization. J Environ Pol Plan 2(4):269–285. https://doi.org/10.1080/714038561

Janowski T (2016) Implementing sustainable development goals with digital government – aspiration-capacity gap. Gov Inform Q 33(4):603–613. https://doi.org/10.1016/j.giq.2016.12.001

Jiang HL, Jiang PC, Wang D, Wu JH (2021) Can smart city construction facilitate green total factor productivity? A quasi-natural experiment based on China's pilot smart city. Sustain Cities Soc 69(3):102809. https://doi.org/10.1016/j.scs.2021.102809

Lange S, Pohl J, Santarius T (2020) Digitalization and energy consumption. Does ICT reduce energy demand? Ecol Econ 176:106760. https://doi.org/10.1016/j.ecolecon.2020.106760

Lee JW, Brahmasrene T (2014) ICT, CO_2 Emissions and economic growth: evidence from a panel of ASEAN. Global Econ Rev 43(2):93–109. https://doi.org/10.1080/1226508X.2014.917803

Lee CC, Zeng ML, Wang CS (2022) Environmental regulation, innovation capability, and green total factor productivity: new evidence from China. Environ Sci Pollut Res 29:39384–39399. https://doi.org/10.1007/s11356-021-18388-0

Lesage J, Pace R (2009) Introduction to spatial econometrics. CRC Press, Boca Raton, FL. Introduction to Spatial Econometrics 1. https://doi.org/10.1201/9781420064254

Li B, Wu SS (2017) Effects of local and civil environmental regulation on green total factor productivity in China: a spatial Durbin econometric analysis. J Clean Prod 153:342–353. https://doi.org/10.1016/j.jclepro.2016.10.042

Li Y, Chen YY, Li Q (2020) Assessment analysis of green development level based on S-type cloud model of Beijing-Tianjin-Hebei. China Renew Sust Energ Rev 133:110245. https://doi.org/10.1016/j.rser.2020.110245

Li Y, Yang XD, Ran QY, Wu HT, Irfan M, Ahmad M (2021) Energy structure, digital economy, and carbon emissions: evidence from China. Environ Sci Pollut Res 28:64606–64629. https://doi.org/10.1007/s11356-021-15304-4

Lin BQ, Chen ZY (2018) Does factor market distortion inhibit the green total factor productivity in China? J Clean Prod 197:25–33. https://doi.org/10.1016/j.jclepro.2018.06.094

Litvinenko VS (2020) Digital economy as a factor in the technological development of the mineral sector. Nat Resour Res 29(3):1521–1541. https://doi.org/10.1007/s11053-019-09568-4

Liu YJ, Dong F (2021) How technological innovation impacts urban green economy efficiency in emerging economies: a case study of 278 Chinese cities. Resour Conserve Recy 169:105534. https://doi.org/10.1016/j.resconrec.2021.105534

Liu RY, Wang DQ, Zhang L, Zhang LH (2019) Can green financial development promote regional ecological efficiency? A case study of China. Nat Hazards 95:325–341. https://doi.org/10.1007/s11069-018-3502-x

Liu KD, Shi DS, Xiang WJ, Zhang WT (2022a) How has the efficiency of China's green development evolved? An improved non-radial directional distance function measurement. Sci Total Environ 815:152337. https://doi.org/10.1016/j.scitotenv.2021.152337

Liu JL, Yu QH, Chen YY, Liu JG (2022b) The impact of digital technology development on carbon emissions: a spatial effect analysis for China. Resour Conserv Recy 185:106445. https://doi.org/10.1016/j.resconrec.2022.106445

Llopis-Albert C, Rubio F, Valero F (2021) Impact of digital transformation on the automotive industry. Technol Forecast Soc 162:120343. https://doi.org/10.1016/j.techfore.2020.120343

Luo K, Liu YB, Chen PF, Zeng MI (2022) Assessing the impact of digital economy on green development efficiency in the Yangtze River Economic Belt. Energ Econ 112:106127. https://doi.org/10.1016/j.eneco.2022.106127

Lyu YW, Zhang JN, Liu SL (2022) The impact of land price distortion on green development efficiency: mechanism discussion and empirical test. Environ Sci Pollut Res. https://doi.org/10.1007/s11356-022-20571-w

Meng M, Qu DL (2021) Understanding the green energy efficiencies of provinces in China: a super-SBM and GML analysis. Energy 239:121912. https://doi.org/10.1016/j.energy.2021.121912

Michaels G, Natraj A, Reenen JV (2014) Has ICT polarized skill demand? Evidence from eleven countries over 25 years. Rev Econ Stat 96(1):60–77. https://doi.org/10.3386/W16138

Omri A (2020) Technological innovation and sustainable development: does the stage of development matter? Environ Impact Asses 83:106398. https://doi.org/10.1016/j.eiar.2020.106398

Paunov C, Rollo V (2016) Has the internet fostered inclusive innovation in the developing world? World Dev 78(1):587–609. https://doi.org/10.1016/j.worlddev.2015.10.029

Popkova EG, Bernardi PD, Tyurina YG, Sergi BS (2022) A theory of digital technology advancement to address the grand challenges of sustainable development. Technol in Soc 68:101831. https://doi.org/10.1016/j.techsoc.2021.101831

Proeger T, Runst P (2020) Digitization and knowledge spillover effectiveness-evidence from the "German Mittelstand." J Knowl Econ 11:1509–1528. https://doi.org/10.1007/s13132-019-00622-3

Rashidi K, Saen RF (2015) Measuring eco-efficiency based on green indicators and potentials in energy saving and undesirable output abatement. Energ Econ 50:18–26. https://doi.org/10.1016/j.eneco.2015.04.018

Sareen S, Haarstad H (2021) Digitalization as a driver of transformative environmental innovation. Environ Innov Soc Tr 41:93–95. https://doi.org/10.1016/j.eist.2021.09.016

Song WF, Han XF (2022) A bilateral decomposition analysis of the impacts of environmental regulation on energy efficiency in China from 2006 to 2018. Energy Strateg Rev 43:100931. https://doi.org/10.1016/j.esr.2022.100931

Song ML, Du JT, Tan KH (2018) Impact of fiscal decentralization on green total factor productivity. Int J Prod Econ 205:359–367. https://doi.org/10.1016/j.ijpe.2018.09.019

Song ML, Xie QJ, Shen ZY (2021) Impact of green credit on high-efficiency utilization of energy in China considering environmental constraints. Energ Policy 153:112267. https://doi.org/10.1016/j.enpol.2021.112267

Sun C, Tong Y, Zou W (2018) The evolution and a temporal-spatial difference analysis of green development in China. Sustain Cities Soc 41:52–61. https://doi.org/10.1016/j.scs.2018.05.006

Szalavetz A (2019) Digitalisation, automation and upgrading in global value chains – factory economy actors versus lead companies. Post-Communist Econ 31(5):646–670. https://doi.org/10.1080/14631377.2019.1578584

Tao F, Zhang HQ, Hu J, Xia XH (2017) Dynamics of green productivity growth for major Chinese urban agglomerations. Appl Energ 196:170–179. https://doi.org/10.1016/j.apenergy.2016.12.108

Thompson P, Williams R, Thomas B (2014) Are UK SMEs with active websites more likely to achieve both innovation and growth? J Small Bus Enterp Dev 20(4):934–965. https://doi.org/10.1108/JSBED-05-2012-0067

Tian XJ, Li R (2022) Digital technology empowers the transformation and development of real economy: an analysis framework based on Schumpeter's endogenous growth theory. J Manage World 5:56–74 (**(in Chinese)**)

Tone K (2004) Dealing with undesirable outputs in DEA: a slacks-based measure (SBM) approach. North American Productivity Workshop, Toronto, pp 44–45

Usai A, Fiano F, Messeni Petruzzelli A et al (2021) Unveiling the impact of the adoption of digital technologies on firms' innovation performance. J Bus Res 133:327–336. https://doi.org/10.1016/j.jbusres.2021.04.035

Wang L, Chen YY, Ramsey TS, Hewings G (2021) Will researching digital technology really empower green development? Technol in Soc 66:101638. https://doi.org/10.1016/j.techsoc.2021.101638

Wang LL, Chen LY, Li YS (2022a) Digital economy and urban low-carbon sustainable development: the role of innovation factor mobility in China. Environ Sci Pollut Res 29:48539–48557. https://doi.org/10.1007/s11356-022-19182-2

Wang JQ, Ma XW, Zhang J, Zhao X (2022b) Impacts of digital technology on energy sustainability: China case study. Appl Energ 323:119329. https://doi.org/10.1016/j.apenergy.2022.119329

Wu HT, Hao Y, Ren SY, Yang XD, Xie G (2021) Does internet development improve green total factor energy efficiency? Evidence from China. Energ Policy 153:112247. https://doi.org/10.1016/j.enpol.2021.112247

Yang LS, Ni MY (2022) Is financial development beneficial to improve the efficiency of green development? Evidence from the "Belt and Road" countries. Energ Econ 105:105734. https://doi.org/10.1016/j.eneco.2021.105734

Yang YF, Wang HR, Wang C, Yang B (2022a) Model-based temporal evolution and spatial equilibrium analysis of green development in China's Yangtze River Economic Belt from 2009 to 2018. Ecol Indic 141:109071. https://doi.org/10.1016/j.ecolind.2022.109071

Yang YP, Wu D, Xu M, Yang MT, Zou WJ (2022b) Capital misallocation, technological innovation, and green development efficiency: empirical analysis based on China provincial panel data. Environ Sci Pollut Res 1–14 https://doi.org/10.1007/s11356-022-20364-1

Yu BB (2022) The impact of the internet on industrial green productivity: evidence from China. Technol Forecast Soc 177:121527. https://doi.org/10.1016/j.techfore.2022.121527

Yuan HX, Zou LH, Feng YD, Huang L (2022) Does manufacturing agglomeration promote or hinder green development efficiency? Evidence from Yangtze River Economic Belt, China. Environ Sci Pollut Res 1–22 https://doi.org/10.1007/s11356-022-20537-y

Zhang HM, Zhu ZS, Fan YJ (2018) The impact of environmental regulation on the coordinated development of environment and economy in China. Nat Hazards 91:473–489. https://doi.org/10.1007/s11069-017-3137-3

Zhang JN, Lyu YW, Li YT, Geng Y (2022a) Digital economy: an innovation driving factor for low-carbon development. Environ Impact Asses 96:106821. https://doi.org/10.1016/j.eiar.2022.106821

Zhang W, Liu XM, Wang D, Zhou JP (2022b) Digital economy and carbon emission performance: evidence at China's city level. Energ Policy 165:112927. https://doi.org/10.1016/j.enpol.2022.112927

Zhao XM, Liu CJ, Yang M (2018) The effects of environmental regulation on China's total factor productivity: an empirical study of carbon-intensive industries. J Clean Prod 179:325–334. https://doi.org/10.1016/j.jclepro.2018.01.100

Zhao PJ, Zeng LE, Lu HY, Zhou Y, Hu HY, Wei XY (2020) Green economic efficiency and its influencing factors in China from 2008 to 2017: based on the super-SBM model with undesirable outputs and spatial Dubin model. Sci Total Environ 741:140026. https://doi.org/10.1016/j.scitotenv.2020.140026

Zheng H, Wu SF, Zhang Y, He Y (2023) Environmental regulation effect on green total factor productivity in the Yangtze River Economic Belt. J Environ Manage 325:116465. https://doi.org/10.1016/j.jenvman.2022.116465

Zhou L, Zhou CH, Che L, Wang B (2020) Spatiotemporal evolution and influencing factors of urban green development efficiency in China. J Geogr Sci 30:724–742. https://doi.org/10.1007/s11442-020-1752-5

Zhu BZ, Zhang MF, Zhou YH et al (2019) Exploring the effect of industrial structure adjustment on interprovincial green development efficiency in China: a novel integrated approach. Energ Policy 134:110946. https://doi.org/10.1016/j.enpol.2019.110946